Design of a Malaria Parasite Detection Model in Microscopic Images of Blood Cells using the Convolutional Neural Network Method

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ABSTRACT
The malaria examination technique through a microscope is the most commonly used examination in health facilities. However, microscopic examination techniques require special skills and take quite a long time. This research aims to develop a malaria parasite detection system model in blood cell images using deep learning technology to increase the accuracy and speed of detection with the Convolutional Neural Network (CNN) algorithm. This research was carried out in several stages consisting of data collection, image preprocessing, dividing training data and validation data, creating a model using CNN, and evaluating the model. A CNN model was created to classify blood cell images into two classes, namely infected and uninfected. The dataset used as a reference in forming a detection system model uses blood cell images from the open-source Kaggle, totaling 11,312 images. The CNN model evaluation results obtained an accuracy value of 97.17% in detecting blood cell images. These results show that the CNN model created can be used to detect malaria parasites using blood cell images.

General Terms
Deep Learning, Detection Model.

Keywords
Convolutional Neural Network, Deep Learning, Malaria

1. INTRODUCTION
Malaria is a disease of concern in Banjarmasin City, South Kalimantan. The government's commitment to handling malaria cases is in line with Minister of Health Decree Number 293 of 2009 concerning Malaria Elimination by 2024 in 405 districts/cities in Indonesia and the Ministry of Health's Strategic Plan 2020-2024 [1]. In 2023, there will be an increase in the number of positive cases of malaria in Banjarmasin, namely, there are 164 cases that have been confirmed positive for malaria based on laboratory results with microscopic examination of the 166 reported cases of suspected malaria. [2].
Microscopic examination is the most common malaria examination technique used in health facilities. Known as an accurate and cheap examination, this examination requires experts to carry it out. Having experienced medical personnel makes it easy to find parasites in blood cells. However, microscopic examination requires special skills and quite a long time. Detection of malaria parasites using traditional microscopic methods takes approximately 30 to 60 minutes, which includes blood sampling, sample preparation and staining, and microscopic examination by a trained laboratory technician [3].
Based on these problems, developing a method for automatic detection of malaria parasites in blood cell images is very important to speed up the diagnosis process and increase the accuracy of results. In this context, deep learning technology has shown great potential in processing and analyzing image data [4]. Deep learning is a field of machine learning that uses artificial neural networks to solve problems with large datasets [5]. Deep learning methods have shown promising results in various fields, including medical image recognition [6].
Along with the development of Artificial Intelligence (AI) technology, malaria can be detected by analyzing microscopic images of blood cells [7]. In microscopic images of blood cells, deep learning algorithms can recognize complex patterns and features, which are difficult for the human eye to detect. The application of AI, especially the deep learning approach, has been widely used in carrying out medical image analysis tasks, including the detection of Dengue Fever [8], Diabetic Retinopathy [9], Brain Tumor [10], and Monkey Pox [11]. The use of technology in disease detection through blood cell image analysis has been carried out by [8] producing methods and systems that can diagnose dengue fever patients by utilizing blood cell smear images, thereby speeding up the diagnosis process and saving costs.
One technique that can be used to build a malaria detection system is to use sophisticated deep learning technology with the Convolutional Neural Network (CNN) algorithm which has the advantage of better visual image recognition [12]. CNN has been proven to provide excellent results in image classification and has been widely used in previous research and has good results [13]. Another study that applied CNN produced an accuracy of 97.14% in classifying image data of healthy and COVID-19-affected lungs [14].
In this research, the CNN algorithm can be used to classify blood cells infected with malaria and not infected with malaria.

2. RESEARCH METHODS
This research was carried out in several stages consisting of data collection, image preprocessing, dividing training data and validation data, creating a model using CNN, and evaluating the model. These steps are illustrated in Figure 1.

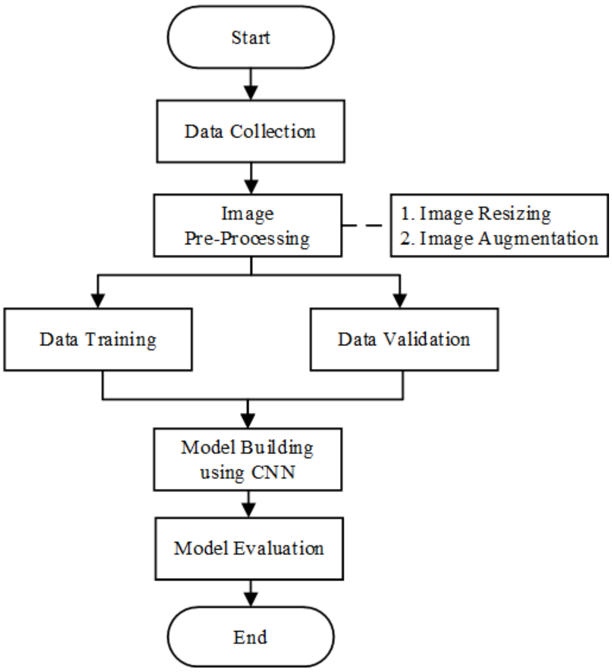

Fig 1: Research Method

2.1 Data Collection
The blood cell image dataset used in this research was taken from the Kaggle open data source of 11.312 blood cell images, with the division seen in Table 1. This dataset is used as a reference for forming a detection system model.

Table 1. Data Collection

Image Category	**Total Training**	**Total Validation**
Parasite images	5043	1111
Uninfected images	4104	1054
Total	**9147**	**2165**

2.2 Image Preprocessing
Preprocessing is an essential step to clean image data before it is ready to be used in a computer vision model. Image preprocessing is the steps taken to format images before they are used by model training and inference. Two things are done at this stage, namely image resizing and image augmentation.

2.2.1 Image Resizing
Image resizing is a step in changing the size of an image to be larger or smaller than the initial image size with a previously determined size. This aims to reduce the computing load and make storage memory usage more efficient. The image size in this study was changed to 224x224 pixels, and the batch size was set to 64.

2.2.2 Image Augmentation
Image augmentation is manipulation applied to images to create different versions of similar content to expose the model to more training examples. Before data augmentation was carried out, there was only one image, but after the data augmentation process was applied, the number of images increased to two or more with several variations such as rotation, shift or enlargement.
Image augmentation manipulation is a form of image preprocessing, but there is an important difference: while image preprocessing steps are applied to both the training and test sets, Image augmentation is only applied to the training data. This technique helps prevent overfitting and improves the generalization of deep learning models [15].

2.3 Training and Validation Data
In this stage, the dataset is divided with a ratio of 80:20, 80% training data, and 20% validation data. Dataset splitting was done manually with care to ensure the dataset was split randomly and proportionally. The dataset consists of 11,312 image data which has been divided into 2 classes, namely "Infected" and "Uninfected", with each class totaling 6,154 data for the "Infected" class and 5,158 data for the "Uninfected" class. After that, the data was divided with a ratio of 80% for training data and produced 9,147 data, and 20% for testing data and produced 2,165 data. Details of the distribution of training data and testing data can be seen in Table 2.

Table 2. Training and Validation Data

Data	**Amount of Data**
Training Infected	5043
Training Uninfected	4104
Validation Infected	1111
Validation Uninfected	1054
Total	**Training = 9147**
	Validation = 2165
	Dataset = 11312

3. LITERATURE REVIEW
3.1 Microscopic Image
Microscopic images are images resulting from photographing objects through a microscope. Microscopic images are often used in research that aims to analyze small structures such as tissues and cells in detail. Microscopic images of blood cells are obtained through photography by placing the patient's blood sample on a microscope to be observed and then photographed using a regular camera or the camera on the microscope.

3.2 Deep Learning
One branch of machine learning is deep learning which uses artificial neural networks to solve problems with very large datasets. Deep learning techniques provide a very powerful structure for supervised learning. Learning models can better describe labeled image data by adding layers. Machine learning training usually takes months, years or even decades to create a complete feature set for manual data classification. The most accurate algorithm currently is deep learning [16].

3.3 Convolutional Neural Network
Convolutional Neural Network (CNN) is one of the algorithms in deep learning. CNN has a way of working by using image or video datasets as input. CNN is often used for research, especially to classify a case study with image objects or image images. CNN uses Multi-Layer Perceptron (MLP) to process and classify images [17].
The CNN architecture consists of an input layer, an output layer, and a hidden layer. The hidden layers are usually part of three main layers, namely the convolutional layer, pooling layer and fully connected layer [18].

4. RESULTS
4.1 Model Building
The detection model was created using the CNN algorithm with a sequential layer architectural model consisting of 2

architectural layers, namely the feature learning and classification layer [19] as seen in Figure 2.

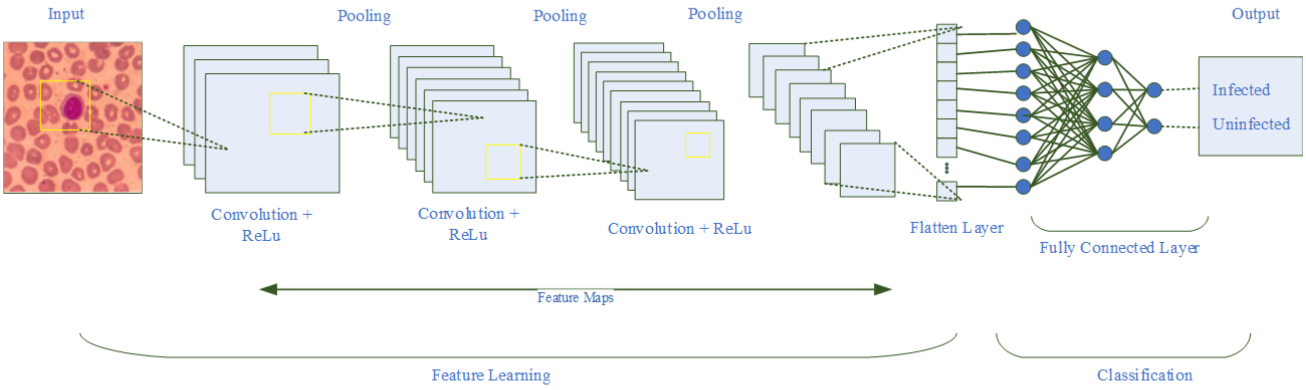

Fig 2: Sequential Model Layer of CNN

In the feature learning section, there is a layer that is useful for receiving image input directly at the beginning and processing it to produce output. The layers in this process consist of convolution layers and pooling layers, where each layer process will produce feature maps in the form of numbers that represent images which are then passed on to the classification layer. The convolutional Layer is the basic layer of CNN, where this layer learns edges, textures, and patterns from the input image while Pooling Layers help prevent overfitting by reducing the number of parameters and reducing the spatial dimensions of the convolutional layer output.

The classification layer consists of several layers containing neurons that are fully connected with other layers (also called dense). This layer receives input from the output layer of the feature learning section which is then processed in flatten with the addition of several hidden layers in the fully connected to produce output in the form of classification accuracy for each class. Information about the layer type, output shape, and number of parameters can be seen in Table 3.

Table 3. Parameter information on the CNN layer

Layer (type)	Output Shape	Parameter
max_pooling2d	(none, 125, 125, 3)	0
conv2d	(none, 123, 123, 32)	896
max_pooling2d_1	(none, 61, 61, 32)	0
conv2d_1	(none, 59, 59, 64)	18,946
max_pooling2d_2	(none, 29, 29, 64)	0
conv2d_2	(none, 27, 27, 64)	36,928
max_pooling2d_3	(none, 13, 13, 64)	0
conv2d_3	(none, 11, 11, 64)	36,928
max_pooling2d_4	(none, 5, 5, 64)	0
flatten	(none, 1600)	819,712
dense	(none, 512)	1026
dense_1	(none, 2)	0

In the first layer (MaxPooling2D) is used to reduce the dimensions of spatial data where the size from (None, 250, 250, 3) becomes (None, 125, 125, 3). The convolution layer (Conv2D) in the first layer is used to extract features from the image by applying filters and produces 32 filters with output sizes (None, 123, 123, 32) and has 896 parameters. Another MaxPooling2D layer reduces the image size after convolution, while the next Conv2D layer adds depth to features and parameters. The Platten layer flattens 2D data into 1D with output (None, 1600). Then the Dense layer uses 819,712 parameters for classification with 512 units, and the next Dense layer uses 1,026 parameters for the final decision.

4.2 Model Evaluation

Before getting accuracy, the model is trained first using a train generator and validation generator. The number of epochs used to train the model is 10, the results of testing model accuracy can be seen in Table 4.

Table 4. Model Evaluation

Iteration	Training		Validation	
	Accuracy (%)	Loss	Accuracy (%)	Loss
1	71.46	0.5359	89.46	0.2986
2	94.49	0.1714	95.33	0.1841
3	95.30	0.1416	96.58	0.1443
4	96.58	0.1112	96.35	0.1452
5	96.91	0.0985	96.49	0.1237
6	96.85	0.1038	96.58	0.1172
7	96.42	0.1031	96.77	0.1152
8	96.64	0.1006	96.40	0.1492
9	96.77	0.1024	96.81	0.1207
10	**97.17**	**0.0871**	**96.95**	**0.1118**

In the first iteration, accuracy on training data (71.46%) was still quite low, but accuracy on validation data was high (89.46%). This is because the model is just starting to learn patterns from the training data. In iterations 2-5: training and validation accuracy continues to increase, while loss continues to decrease. This shows that the model is getting better at learning patterns from training data and generalizing to validation data. In iterations 6-10: the model achieves high accuracy on both training (around 96-97%) and validation data (around 96%), with increasingly lower loss. This shows that the model has achieved stable performance, and there is no significant change in accuracy or loss after all iterations. The results of evaluating training and validation accuracy with epoch 10 can also be seen in Figure 3.

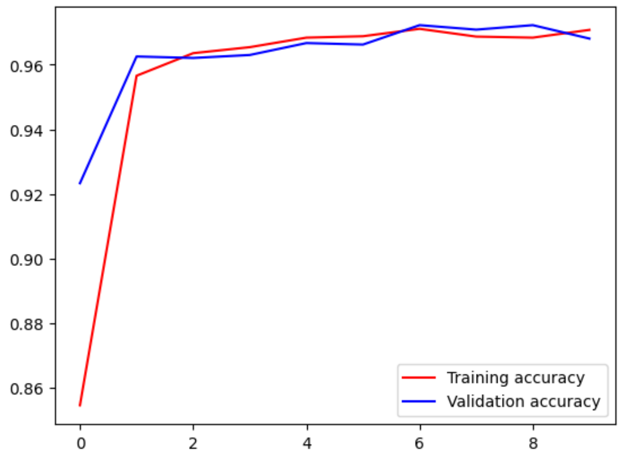

Fig 3: Training and Validation Accuracy

The model evaluation results show quite good results with an accuracy of 97.17%. The validation accuracy results remain high and stable, and the validation loss is low, indicating that there is no significant overfitting.

5. CONCLUSIONS

The conclusions from the research that has been carried out are as follows:

1) The CNN model uses four layers: Convulsion Layer, Pooling Layer, Fully Connected Layer, and Scaling layer. The model consists of several convolution and pooling layers, which are then flattened and passed to the fully connected layer for classification.
2) The number of parameters shows that this model is quite complex and can extract many features from images.
3) The deep learning model using the CNN algorithm can detect malaria parasites using blood cell images with an accuracy of 97.17% with epoch 10.
4) The overall research results have a fairly good level of accuracy, so they can be integrated into a detection system and considered for field clinical trials. After the verification process, the system is expected to be able to help various parties early detection of malaria.

6. ACKNOWLEDGMENTS

Thank you to the Ministry of Education, Culture, Research and Technology for the support and funding provided through the Beginning Lecturer Research Grant. Profound thanks are also expressed to all relevant institutions for their cooperation and contributions during the research process. Furthermore, the deepest appreciation is expressed to Sari Mulia University, especially the Faculty of Science and Technology, which has provided a conducive environment and continuous support in this effort.

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